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THESIS

OPTIMIZED POSITIONING OF
PRE-DISASTER RELIEF FORCE AND ASSETS
by

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December 2006

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Recent events in the United States of America and Pakistan have exposed the shortcomings of existing planning in relief and humanitarian assistance in the face of large-scale natural disasters. This thesis develops a two-stage stochastic optimization model to provide guidance in the pre-positioning of relief units and assets, where budget, physical limitations and logistics are taken into account. Stochastic data include the number of survivors in each potential affected area (AA), the amount of commodities that needs to be delivered to each AA and the transportation time from each relief location (which reflects scenarios where, for example, roads are blocked). As first-stage decisions, we consider the expansion of warehouses, medical facilities and their health care personnel, as well as ramp space to facilitate aircraft supply of commodities to the AAs. The second-stage is a logistic problem represented as a network, where maximizing expected rescued survivors and delivery of required commodities are the driving goals. This is accomplished through land, air and sea transportation means (e.g., CH-53 helicopters configured for rescue missions), as well as relief workers. The model has been successfully assessed on notional scenarios and is expected to be tested on realistic cases by personnel who are involved in relief planning.

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**OPTIMIZED POSITIONING OF
PRE-DISASTER RELIEF FORCE AND ASSETS**

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Submitted in partial fulfillment of the
requirements for the degree of

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ABSTRACT

Recent events in the United States of America and Pakistan have exposed the shortcomings of existing planning in relief and humanitarian assistance in the face of large-scale natural disasters. This thesis develops a two-stage stochastic optimization model to provide guidance in the pre-positioning of relief units and assets, where budget, physical limitations and logistics are taken into account. Stochastic data include the number of survivors in each potential affected area (AA), the amount of commodities that needs to be delivered to each AA and the transportation time from each relief location (which reflects scenarios where, for example, roads are blocked). As first-stage decisions, we consider the expansion of warehouses, medical facilities and their health care personnel, as well as ramp space to facilitate aircraft supply of commodities to the AAs. The second-stage is a logistic problem represented as a network, where maximizing expected rescued survivors and delivery of required commodities are the driving goals. This is accomplished through land, air and sea transportation means (e.g., CH-53 helicopters configured for rescue missions), as well as relief workers. The model has been successfully assessed on notional scenarios and is expected to be tested on realistic cases by personnel who are involved in relief planning.

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LIST OF TERMS AND ABBREVIATIONS

AA	Affected Area
CH-53, MV-22	Aircraft employed for relief operations
CH-53G, CH-53S	CH-53 configured for "general" and "special" mission, respectively
EVPI	Expected Value of Perfect Information
HMMWV	High-Mobility Multipurpose Wheel Vehicle
HP	Health Personnel
MV-22G, MV-22S	MV-22 configured for "general" and "special" mission, respectively
POM	Pre-positioning Optimization Model
PS	Potential Survivor
RL	Relief Location
RS	Ramp Space
RUA	Relief Units and Assets
TM	Transportation Means
VSS	Value of Stochastic Solution
"General" mission	Transportation of commodities and relief workers
"Special" mission	Transportation of rescued survivors

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EXECUTIVE SUMMARY

Recent events in the United States of America and Pakistan have exposed the shortcomings of existing planning in relief and humanitarian assistance in the face of large-scale natural disasters. Shortcomings include factors like poorly pre-positioned relief units and assets, insufficient budget allocated, and poor post-disaster relief planning. These contributed to long response time, which in turn caused the delay of medical evacuation and supply of commodities, and perhaps the death of hundreds of potential survivors.

We develop a two-stage, linear, mixed-integer program called Pre-positioning Optimization Model (POM) to provide guidance in the pre-positioning of relief units and assets, where budget, physical limitations and logistics are taken into account. Stochastic data include the number of survivors in each potential affected area (AA), the amount of commodities that needs to be delivered to each AA, and the transportation time from each relief location (which reflects scenarios where, for example, roads are blocked).

As first-stage decisions, we consider the expansion of warehouses, medical facilities and their health care personnel, as well as ramp space to facilitate the supply of commodities by aircraft to the AAs. These decisions are termed first-stage as their implementation must be carried out well in advance, before a disaster strikes. The second-stage is a logistic problem represented as a network, where maximizing expected rescued survivors and delivery of required commodities are the driving goals. This is accomplished through land, air and sea transportation means (e.g., CH-53 helicopters configured for rescue missions), as well as relief workers. An unmet commodity penalty is built in the objective function to penalize the total number of rescued survivors.

We implement POM in the General Algebraic Modeling System and use CPLEX as the solving engine. Two hypothetical test cases (Earthquake and Hurricane) are used for testing. To simulate the different levels of disaster severity, each test case has its distinct set of scenario data (e.g., number of potential survivors, demand of commodities and impassable roads) and a hypothetical probability. A bound on the optimal stochastic

solution is obtained by solving POM with perfect information (i.e., as a weighted average of the deterministic solutions for each scenario). The optimal stochastic solution is also compared with a heuristic solution based on the optimal plan for an "average scenario."

The benefits of solving POM using stochastic optimization are apparent: total number of rescued survivors (after penalties for unmet commodities are accounted for) is improved by 11% and 37% in the earthquake and hurricane test cases, respectively, with respect to the heuristic solution. But even if a deterministic scenario were considered, finding an optimal solution without POM would be nearly impossible.

POM can be used as a tool to aid in planning budget allocation, sitting of relief forces, and pre-positioning of warehouses and other assets. We recommend further study using validated data. Our tool is expected to be used by personnel who are involved in relief planning.

I.   INTRODUCTION

The term disaster usually evokes images of massive material damage and great human distress caused by some swift catastrophe. A disaster can be defined as a sudden event that disrupts the social structure, and prevents execution of some or all of the social structure's essential functions [Foster, 1983]. Disaster may surprise rich and poor alike, and show how even highly capable governments are unprepared to deal with the massive exigencies of emergency relief. Recent natural disasters in the Pakistan [Wikipedia, 2006] and the United States of America [Wikipedia, 2005] exposed the shortcomings of existing planning at both domestic and international cooperation levels. In the above examples, the affected area's authorities lacked the manpower and logistic preparation to assemble and coordinate sufficient teams to aid in the humanitarian rescue.

Humanitarian planning and assistance is a large-scale process that requires the collaboration and coordination of government agencies and other organizations. For example, in the U.S., participants include the Federal Emergency Management Agency, the National Guard and other military forces [U.S. Army, 2005], as well as the American Red Cross and Food for the Hungry [OPM, 2006]. These teams often operate in a complicated environment that includes temporally and spatially varying demand patterns, administrative, legal, and political constraints; and ill-defined objectives [Chaiken and Larson, 1972]. Unpreparedness results in the inability to handle "chaos," which in turn increases the loss of lives.

In an emergency response situation, it is critical to minimize the response time, because each minute wasted diminishes the chances of rescuing potential survivors. Therefore, strategic positioning of relief units (e.g., medical facilities and health care personnel) and assets (e.g., CH-53 helicopters configured for rescue missions) becomes crucial. Unfortunately, it is impossible to place relief units and assets (RUAs) everywhere. A new 464-bed hospital costs around $550 million (Department of Medicine, John Stroger Hospital, 2004), a general doctor costs around $420 per day [Yam, 2004], a new CH-53 cost $25 million in 1993 (FAS 1999), and a new 30,000-square-foot (approximately half the size of an American Football pitch), one-story

warehouse costs around $2.3 million [Department of Commerce and Economic Opportunity, 2004]. It is clear that we can afford only a limited number of each of these assets. Common sense dictates to position RUAs "close to the probable affected areas" where a natural disaster may strike. On the other hand, it also appears reasonable to scatter the RUA locations to enable partial coverage of multiple affected areas by a RUA location, and simultaneous coverage of each possible affected area by multiple RUAs (e.g., to avoid dependency on a single RUA in case it is not accessible after the disaster).

During the first few days after a disaster, influx of logistics also poses a challenge. Logistic infrastructure requires pre-positioning of warehouses and ramp space for aircraft to deliver massive amounts of commodities to the affected areas. "Emergency/Relief Logistics is the basic task of a logistics system: to deliver the appropriate supplies, in good condition, in the quantities required, and at the places and the time they are needed. Relief Logistics encompass the relocation of disaster affected people, transfer of casualties, and the movement of relief workers" [Hanaoka and Qadir, 2005]. These logistical implications have been studied by many researchers, such as Darcy [2005], who discusses the problems in accessing the affected areas in the Indian Ocean tsunami crisis in 2004.

Modeling the needs before and after a disaster is a complicated process and the complication becomes increasingly intricate by the large amount of RUAs involved. For example, the transportation means can be land, air and/or sea. The number of transportation means needed will hinge on the budget. Expansion of warehouses, medical facilities, ramp space for aircraft and many more considerations are factors that will affect the budget allocation directly. This thesis develops mathematical models to help strike a balance among these considerations.

The analysis focuses on the strategic level planning of humanitarian disaster relief, which guides the budget allocation and positioning of RUAs in order to maximize the number of expected survivors.

The positioning of RUAs has similar challenges to the positioning of facilities (see, for example, Shmoys et al. [1997]), particularly the positioning of emergency assets, such as fire houses or ambulances, which has evolved since the mid-1960s. The first

models proposed were integer linear programming formulations, as noted by Toregas et al. [1971], who introduce the "location set covering model" to minimize the number of ambulances needed to cover all demand points assuming one type of ambulance and unlimited units. Church and ReVelle [1974] propose an alternative approach to maximize population coverage subject to limited ambulance availability. Both models assume a demand is covered if and only if there exists at least one available unit within a specified distance from its location. This assumption is valid if all demands require just one unit to respond to them. However, in a relief operation, demands often require response from multiple units. In other words, an affected area often requires responses from several RUA locations and for different purposes. Alsalloum and Rand [2006] have developed a model that looks into identifying the optimal locations of a specified number of emergency medical service stations. This model extends the original maximal covering location model stated above and considers factors such as people in distress and the response time required. These additional factors are taken into account in this thesis, such as the need for commodities, transportation capacity, ramp space and different transportation means. Hale and Moberg [2005] introduce a selection model for emergency resources that can be utilized by logistics managers and supply chain continuity teams to determine the appropriate number and locations of storage areas for critical emergency equipments and supplies.

A typical disaster has an unpredictable nature in terms of location, time, and magnitude. Therefore it is worth modeling the disaster's stochastic nature. Liu and Fan [2006] use a two-stage stochastic methodology to model the retrofitting of highway bridges, where the objective is to minimize the expected system loss. This problem is similar to the one addressed in this thesis in terms of the underlying idea: maximizing the number of rescued survivors. However, a key difference is that, in their study, Liu and Fan look into the strategic resource allocation for critical infrastructure protection and hazard prevention, whereas this thesis studies the allocation and expansion of RUAs.

Many simulation models have been developed to represent how pre-established RUAs will respond to disaster relief operations. For example, Marecki et al. [2005] look at the interactions between agents and humans during a disaster response using an agent-

based simulation. This level of detail is catered more toward operational logistics and does not determine the positioning of RUAs, which is assumed given data.

The impetus of this thesis is to develop and solve mathematical optimization models to provide guidance in the decision-making process of pre-positioning RUAs for disaster relief.

We claim the selection of optimal position for RUAs and maximization of rescued survivors can be guided with a two-stage stochastic optimization model. The contribution of this thesis is two-fold: First, the models we have developed integrate the interplays among multiple entities: we differentiate between potential survivors in need of emergency evacuation and homeless people in need of commodities, and consider their spatial location (albeit aggregated by proximity); we account for different transportation means and their transportation logistics, including operating time, routing, capacity (for workers, commodities and evacuees), and landing needs (if applicable); and we represent the location of health personnel, warehouses and ramp spaces, and allow for their budget-constrained expansion. We are not aware of any model that explicitly incorporates all of these aspects. Second, we account for uncertainty in the problem data by separating strategic decisions (to be made now) from operating decisions (which are scenario dependent), and demonstrate the benefits of the two-stage approach versus planning for a single scenario. While there are multiple models in the area of two-stage stochastic programming (some described above), none of them specifically address the problem of strategic pre-positioning of RUAs.

The remainder of this thesis is organized as follows: In Chapter II, we develop and describe the mathematical formulation of the pre-positioning model. Chapter III describes our test cases and assumptions. Results for these cases are reported in Chapter IV. Chapter V provides conclusions and identifies areas for future research.

II. A MODEL FOR OPTIMIZED PRE-POSITIONING OF RELIEF UNITS AND ASSETS

A. OVERVIEW

This chapter introduces the Pre-positioning Optimization Model (POM). First, it is important to develop a deterministic model which considers the following fundamental data:

- A set of affected areas (AAs) and relief locations (RLs);

- Potential survivors (PSs) in each AA;

- Commodities needed in each AA;

- Workers required to handle commodities in each AA;

- Available health personnel (HP) and warehouses at each RL;

- Available ramp space (RS) at each AA;

- Available transportation means (TM), with associated capacity for survivors, commodities and relief workers, time to travel between the AAs and the RLs, available operating hours and operating range; and,

- Allocated budget for pre-positioning of additional HP, warehouses, RS and post-disaster engagement of transportation means.

AAs represent areas hit by the disaster and RLs represent RUA locations, which are usually located away from the AAs. In this thesis, it is assumed that PSs are people who survive the disaster and need medical evacuation from an AA. For simplicity, all PSs are assumed to have the same priority to be rescued.

PSs are picked up only by TM configured for "special" mission, which depicts a TM that can transport injured people but is not configured to deliver commodities. As opposed to these, TM configured for "general" mission deliver only commodities and relief workers. Each TM's travel time depends on the distance between the AA and the RL, the TM's speed and the severity of the scenario, which may delay or even impede traveling. Land-based TM may not be able to travel to every RL due to damaged or

impassable roads. Also, some TM are not allowed to use specific RLs, for example, if the TM is an aircraft and the RL does not have an adequate runway or a helipad. Each TM is capable of performing multiple trips, but it is restricted by its available operating hours. Certain TM, such as the CH-53, require ramp space in order to deliver commodities to an AA. Land-based TMs, such as High-Mobility Multipurpose Wheeled Vehicle (HMMWV) (U.S. Army, 2006) do not require ramp space as they are very mobile and are assumed to be able to unload their commodities directly to the homeless people in the AA.

It is assumed that every homeless person in an AA is in need of commodities. Not meeting this need will cause a deterioration in health, resulting in an increase in the number of deaths. In order to capture this feature, we have introduced a penalty function.

Unloading and organizing the commodities in AAs requires relief workers' intervention. Therefore, commodities are accompanied by relief workers and they share capacity on "general" mission TM according to a linear relationship.

Total cost associated with the expansion of medical facilities and associated HP, warehouses, RS, and additional TM is limited by a total allocated budget.

Stochastic programming provides the platform for modeling optimization problems under uncertainty. Our problem is modeled via two-stage stochastic optimization. The decision variables of this model are split into two sets. The first set of variables (first-stage) is decided before the disaster strikes. The second set of variables (second-stage) is based on the concept of recourse: the ability to take corrective actions after an uncertain event has taken place. Under the paradigm of a recourse model, we have to make some decisions: expansion of warehouses, medical facilities and RS. Then, we maximize the expected number of rescued survivors based on the consequences of those decisions and the possible values of the random, second-stage variables. These are dependent on the scenario which characterizes uncertainty: number of PSs at each AA, the demand of commodities which is driven by number of homeless people; and the accessibility to the AAs.

In addition to the above strategic decisions, the model output provides details on expenditure of budget, number of rescued survivors, amount of commodity delivered,

number of relief workers needed, number of TM required and the TM's approximate number of trips between the RLs and the AAs.

B. PRE-POSITIONING OPTIMIZATION MODEL

Pre-positioning optimization model (POM) is a two-stage, linear, mixed-integer stochastic model. We assume POM looks into pre-positioning decisions in preparation for the surge (e.g., within three days after a disaster strikes) of relief operations. Additional modeling assumptions are discussed in Chapter III. The POM formulation follows:

Indices and Index Sets:

A,	Set of affected areas; $a \in A = \{1, 2, 3, ...\}$
L,	Set of starting and drop off relief locations l; $l' \in L = \{1, 2, 3, ...\}$
T,	Set of transportation means; $t \in T = \{\text{CH-53, MV-22, HMMWV}\}$
$T_l^L \subset T$,	Subset of transportation means that can depart from or drop off at relief location l
$T^R \subset T$,	Subset of transportation means that requires ramp space
Ω,	Set of scenarios; $\omega \in \Omega = \{1, 2, 3, ...\}$

Parameters and units:

Scenario-dependent Data

$dcom_a^{\omega}$, Tonnage of commodities needed in affected area a under scenario ω [tons]

$dsur_a^{\omega}$, Number of potential survivors in affected area a under scenario ω [survivors]

t^{ω}_{tla} Time taken for transportation means t to travel from relief location l to affected area a under scenario ω [hours / trip]

wpc^{ω}, Relief workers per ton to handle commodities at affected area a under scenario ω [workers / ton]

p^{ω}, Probability of scenario ω occurring

Survivor Data

$hpps$, Number of survivors that a health personnel can handle [survivors / health personnel]

$ichpps_l$, Initial number of health personnel of relief location l [health personnel]

$maxehpps_l$, Maximum expansion for health personnel at relief location l [health personnel]

$vechpps_l$, Variable expansion cost for health personnel at relief location l [$ / health personnel]

Ramp Space Data

icr_a, Initial ramp space capacity at affected area a [tons]

$maxer_a$, Maximum expansion for ramp space at affected area a [tons for three days]

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$vecr_a$,   Variable expansion cost for ramp space at affected area a

                         [$ / ton]

Commodity Data

icc_l,   Initial capacity for commodities at relief location l [tons]

$maxec_l$,   Maximum expansion for commodities at relief location l

                         [tons]

$vecc_l$,   Variable expansion cost for commodities at relief location l

                         [$ / ton]

Transportation Means Data

ict_t,   Initial number of units of transportation means t [number of

                         units]

$maxet_t$,   Maximum expansion for transportation means t [units for

                         three days]

$vect_t$,   Variable expansion cost for additional unit of transportation

                         means t [$ / unit]

$comcap_t$,   Commodity capacity of "general" transportation means t (if

                         loaded with cargo only) [tons / transportation means × trip]

$wcap_t$,   Relief worker capacity of "general" transportation means t

                         (if loaded with relief workers only)

                         [workers / transportation means × trip]

$scap_t$,   Survivor capacity of "special" transportation means t

                         [survivors / transportation means × trip]

h_t,   Daily available hours of transportation means t

                         [hours / aircraft × day]

r_t,   Operating range of transportation means t [hours]

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$b,$ Total budget allocated [$]

$qc,$ Penalty by unmet commodities (i.e., qc homeless people are assumed to perish per ton of unmet commodities) [survivors / ton]

Derived Sets and Data:

$L^S \subset L,$ Subset of relief locations where survivors could be dropped off;

derived as $\left\{ l \in L \middle| ichpps_l > 0 \text{ or } maxehpps_l > 0 \right\}$

$L^C \subset L,$ Subset of relief locations from where commodities could be supplied;

derived as $\left\{ l \in L \middle| icc_l > 0 \text{ or } maxec_l > 0 \right\}$

$A^R \subset A,$ Subset of affected areas where ramp space exits or may exist;

derived as $\left\{ a \in A \middle| icr_a > 0 \text{ or } maxer_a > 0 \right\}$

$T^G \subset T,$ Subset of transportation means used for "general" missions;

derived as $\left\{ t \in T \middle| scap_t = 0 \right\}$

$T^S \subset T,$ Subset of transportation means used for "special" missions;

derived as $\left\{ t \in T \middle| scap_t > 0 \right\}$

$K \subset T \times L \times A \times L,$ Subset of four-tuples (t, l, a, l') where it is feasible for transportation means t to travel from l to a and then to l'; derived as

$$\left\{ (t,l,a,l') \in T \times L \times A \times L \middle| t_{tla} + t_{tl'a} \le r_t,\ t \in T_l^L \cap T_{l'}^L \right\}$$

$K^G \subset K,$ Subset of four-tuples (t,l,a,l') $\middle| (t,l,a,l') \in K, t \in T^G, l \in L^C$

where it is feasible for "general" transportation means t to travel from l to a and then to l'.

$K^S \subset K,$ Subset of four-tuples (t,l,a,l') $\middle| (t,l,a,l') \in K, t \in T^S, l \in L^S$

where it is feasible for "special" transportation means t to travel from l to a and then to l'.

ics_l Initial capacity for survivors at relief location l [survivors];

calculated as $ics_l = ichpps_l \times hpps$

$maxes_l$ Maximum expansion for survivors at relief location l [survivors];

calculated as $maxes_l = maxehpps_l \times hpps$

$vecs_l$ Variable expansion cost for survivors at relief location l [$];

calculated as $vecs_l = vechpps_l / hpps$

Decision variables and units:

Commodity Decision Variables

$COMD^{\omega}_{tlal'}$,   Commodities delivered by transportation means t traveling

from l to a and then l' under scenario ω [tons]

$TCOMD^{\omega}_{ta}$,   Total commodities delivered by transportation means t to

affected area a under scenario ω [tons]

UC^{ω}_a,   Unmet commodities at affected area a under scenario ω

[tons]

EC_l,   Expansion needed for commodities at drop off relief

location l [tons]

Survivor Decision Variables

$NSURR^{\omega}_{tlal'}$,   Number of survivors rescued by transportation means t

traveling from l to a and then l' under scenario ω

[survivors]

$TNSURR^{\omega}_{ta}$,   Total number of survivors rescued by transportation means

t at affected area a under scenario ω [survivors]

ES_l,   Expansion needed for survivors at drop off relief location l

[survivors]

Ramp Space Decision Variables

ER_a,   Expansion needed for ramp space at affected area a [tons]

Transportation Means Decision Variables

ETM_t^ω,   Additional transportation means t needed under scenario ω [number of units]

$NTRIP_{tlal'}^\omega$,   Number of trips from l to a and then to l' by transportation means t under scenario ω [trips]

TWD_{ta}^ω,   Number of relief workers carried by transportation means t to affected area a under scenario ω [workers]

Formulation:

$$(1) \quad \max \sum_{\omega} p^{\omega} \left(\sum_{t \in T^S} \sum_{a} TNSURR_{ta}^{\omega} - \sum_{a} qcUC_a^{\omega} \right)$$

Subject to:

Budget Constraint

 - Total budget:

$$(2) \quad \sum_{l \in L^S} vecs_l \, ES_l + \sum_{l \in L^C} vecc_l \, EC_l + \sum_{a \in A^R} vecr_a \, ER_a + \sum_{t} vect_t \, ETM_t^{\omega} \leq b \qquad \forall \omega$$

Commodity Constraints

 - Maximum expansion:

$$(3) \quad EC_l \leq maxec_l \qquad\qquad\qquad\qquad\qquad \forall l \in L^C$$

 - Maximum supply:

$$(4) \quad \sum_{(t,a,l')|(t,l,a,l') \in K^G} COMD_{tlal'}^{\omega} \leq icc_l + EC_l \qquad\qquad \forall l \in L^C, \omega$$

 - Route capacity:

$$(5) \quad COMD_{tlal'}^{\omega} \leq comcap_t \, NTRIP_{tlal'}^{\omega} \qquad\qquad \forall t,l,a,l' | (t,l,a,l') \in K^G, \omega$$

 - Total tonnage:

$$(6) \quad TCOMD_{ta}^{\omega} = \sum_{(l,l')|(t,l,a,l') \in K^G} COMD_{tlal'}^{\omega} \qquad\qquad \forall t \in T^G, a, \omega$$

 - Meet demand:

$$(7) \quad \sum_{t \in T^G} TCOMD_{ta}^{\omega} + UC_a^{\omega} = dcom_a^{\omega} \qquad\qquad \forall a, \omega$$

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Transportation Means Constraints

- Maximum extra units:

$$(8) \quad ETM_t^\omega \leq maxet_t \qquad\qquad \forall t, \omega$$

- Operating hours:

$$(9) \quad \sum_{(l,a,l')|(t,l,a,l')\in K} \left(t_{tla} + t_{tl'a}\right) NTRIP_{tlal'}^\omega \leq h_t \left(ict_t + ETM_t^\omega\right) \qquad\qquad \forall t, \omega$$

- Balance at RLs :

$$(10) \quad \sum_{(a,l')|(t,l,a,l')\in K} NTRIP_{tlal'}^\omega = \sum_{(l',a)|(t,l,a,l')\in K} NTRIP_{tal'l}^\omega \qquad\qquad \forall l, t \in T_l^L, \omega$$

Survivors Constraints

- Maximum expansion:

$$(11) \quad ES_l \leq maxes_l \qquad\qquad \forall l \in L^S$$

- Maximum capacity:

$$(12) \quad \sum_{(t,l,a)|(t,l,a,l')\in K^S} NSURR_{tlal'}^\omega \leq ics_{l'} + ES_{l'} \qquad\qquad \forall l' \in L^S, \omega$$

- Route capacity:

$$(13) \quad NSURR_{tlal'}^\omega \leq scap_t NTRIP_{tlal'}^\omega \qquad\qquad \forall t, l, a, l' \,|\, (t,l,a,l') \in K^S, \omega$$

- Total survivors:

$$(14) \quad TNSURR_{ta}^\omega = \sum_{(l,l')|(t,l,a,l')\in K^S} NSURR_{tlal'}^\omega \qquad\qquad \forall t \in T^S, a, \omega$$

- Maximum survivors:

$$(15) \quad \sum_{t \in T^S} TNSURR_{ta}^\omega \leq dsur_a^\omega \qquad\qquad \forall a, \omega$$

Relief Workers Constraints

    - Relief workers follow commodities:

$$(16) \quad \sum_{t \in T^G} TWD_{ta}^{\omega} \geq wpc^{\omega} \sum_{t \in T^G} TCOMD_{ta}^{\omega} \qquad\qquad \forall a, \omega$$

    - Joint capacity on TM:

$$(17) \quad wcap_t TCOMD_{ta}^{\omega} + comcap_t TWD_{ta}^{\omega} \leq$$

$$wcap_t comcap_t \sum_{(l,l')|(t,l,a,l') \in K^G} NTRIP_{tlal'}^{\omega} \qquad \forall a, t \,|\, t \in T^G, \omega$$

Ramp Space Constraints

    - Maximum expansion:

$$(18) \quad ER_a \leq maxer_a \qquad\qquad \forall a \in A^R$$

    - Maximum capacity:

$$(19) \quad \sum_{t \in T^R} TCOMD_{ta}^{\omega} \leq icr_a + ER_a \qquad\qquad \forall a \in A^R, \omega$$

Non - negative Variables :

$$(20) \quad COMD_{tlal'}^{\omega}, \qquad\qquad \forall t,l,a,l' \,|\, (t,l,a,l') \in K^G, \omega$$

$$TCOMD_{ta}^{\omega}, \qquad\qquad \forall t \in T^G, a, \omega$$

$$UC_a^{\omega}, \qquad\qquad \forall a, \omega$$

$$EC_l, \qquad\qquad \forall l \in L^C$$

$$NSURR_{tlal'}^{\omega}, \qquad\qquad \forall t,l,a,l' \,|\, (t,l,a,l') \in K^S, \omega$$

$$TNSURR_{ta}^{\omega}, \qquad\qquad \forall t \in T^S, a, \omega$$

$$ES_l, \qquad\qquad \forall l \in L^S$$

$$ER_a, \qquad\qquad \forall a \in A^R$$

$$TWD_{ta}^{\omega}, \qquad\qquad \forall t \in T^G, a, \omega$$

Non - negative Integer Variables :

$$(21) \quad NTRIP_{tlal'}^{\omega}, \qquad\qquad \forall t,l,a,l' \,|\, (t,l,a,l') \in K, \omega$$

$$ETM_t^{\omega}, \qquad\qquad \forall l \in T_l^L, \omega$$

C.   MODEL DESCRIPTION

1.   Objective Function (1)

POM seeks to maximize the total expected number of rescued survivors, by all TM and from all AAs. However, a penalty is applied if unmet commodities at the AAs occur.

2.   Budget Constraint (2)

This constraint ensures the allocated budget is not exceeded. It consists of first-stage decisions for expansion of HP, warehouses and RS, and second-stage decisions for the use of extra TM from the available fleet.

3.   Commodity Constraints (3)–(7)

Constraint (3) ensures the allowable warehouse expansion for commodities does not exceed the given maximum expansion.

Constraint (4) limits the commodities that can be delivered from the eligible warehouses to the final capacity of the warehouses (after expansion, if any).

Constraint (5) ensures the commodities carried by each TM (configured for "general" mission) traveling on a given route do not exceed the TM's capacity, which depends on the trips the TM makes on that route.

Constraints (6) and (7) ensure the total amount of delivered commodities does not exceed demand, and account for unmet demand, if any. The latter is penalized in the objective as described above.

4.   Transportation Means Constraints (8)–(10)

Constraint (8) ensures additional TM used do not exceed the maximum available of each type.

Constraint (9) ensures the total travel time per TM does not exceed the available operating hours of the total (initial plus additional) units of that TM type.

Constraint (10) is a flow-balance constraint for TM in and out each RL.

5. Survivors Constraints (11)–(15)

Constraint (11) ensures the allowable HP expansion does not exceed a given maximum. See the derivation of survivor's data based on HP data in the "Derived Sets and Data paragraph.

Constraint (12) limits the number of survivors that can be treated in the eligible medical facilities (i.e., those located in the respective RLs) based on initial plus expanded HP.

Constraint (13) ensures the survivors carried by each TM, configured for special mission, traveling on a given route do not exceed the TM's capacity, which depends on the trips the TM makes on that route.

Constraints (14) and (15) ensure the number of total rescued survivors does not exceed PSs demand at each AA.

6. Relief Workers Constraints (16) and (17)

Constraint (16) ensures relief workers arrive at the AAs at a given rate based on the amount of commodities supplied to the AA.

Constraint (17) depicts total capacity on a "general" mission TM as a linear relationship between relief workers and commodities.

7. Ramp Space Constraints (18) and (19)

Constraint (18) ensures the allowable RS expansion does not exceed its maximum expansion. This constraint is only applicable for RS in AAs where RS exists or may exist.

Constraint (19) ensures the total tonnage of delivered commodities does not exceed the initial RS and the expanded RS, if any, in each AA.

8. Domains for Decision Variables (20) and (21)

These constraints define the appropriate domains for the non-negative and non-negative integer variables.

III. TEST CASE DESCRIPTION AND ASSUMPTIONS

This thesis evaluates two notional test cases, which correspond with relief operations in an earthquake and a hurricane disaster, respectively. Within each test case, two scenarios describe uncertainty.

A. COMMON DATA AND ASSUMPTIONS

1. Operation Period

A typical disaster relief operation will operate throughout days and nights for as long as needed until the devastated area returns to normalcy. In this model, we assume the only restriction from round-the-clock operation is the respective TM's daily operating hours. In an actual relief operation, the number of working hours maybe hindered by poor relief operation planning, long decision cycle from policy makers, aftershocks of an earthquake, other logistic delays and social unrest. Typically in a disaster relief operation, the first few days after a disaster struck will be the most chaotic. Our scenarios look at a hypothetical surge period consisting of the first three days after a disaster.

2. Setup of Affected Areas and Relief Locations

We consider a fictitious area which is divided into two AAs—a_1 and a_2— and four RLs—l_1, l_2, l_3 and l_4. See Figure 1. The details of each RL and AA will be described in the following sections.
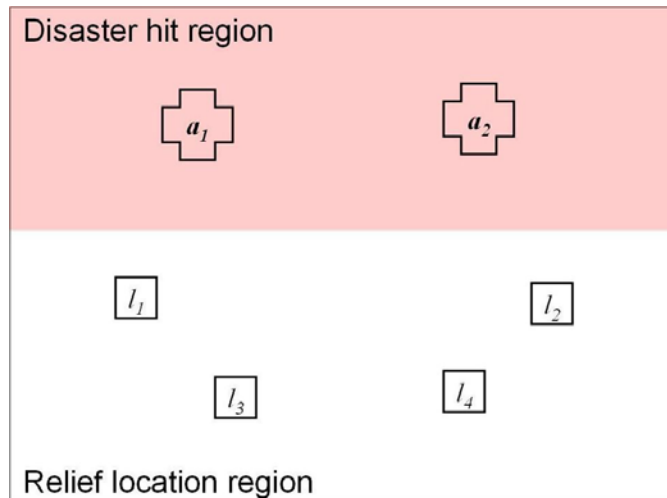

Figure 1. **Affected areas and relief locations**

3. Affected Areas

Three attributes in a typical AA are discussed in this thesis: PS, demand for commodities (and associated relief workers) and RS. An overview of our test cases follows:

a. Potential Survivors

PSs are survivors in need of medical evacuation. For simplicity, we suppose every PS in an AA has equal priority to be rescued. For example, a PS who has a severe head injury and a PS who has broken his leg shares equal priority to be evacuated. We assume the number of PSs in each test case based on the actual fatalities of a disaster of that type [Wikipedia, 2005] and [Wikipedia, 2006]. See Table 1.

Affected area	Earthquake test case		Hurricane test case	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
a_1	70,000	20,000	12,500	20,000
a_2	30,000	80,000	12,500	5,000

Table 1.   **Potential survivors by test case and scenario [survivors]**

b. Demand for Commodities and Relief Workers

We assume the amount of commodities needed is driven by the number of homeless people who are not in need of emergency medical evacuation but require food, medicines, blankets, etc. Not meeting this demand will result in an aggravated condition or even death. See Table 2. In this thesis, we have assumed a penalty factor: $qc = 10$ causalities per ton of unmet commodities.

Relief workers are required to unload and organize the commodities once a TM reaches an AA. They are only allowed to travel on TM configured for "general" mission, sharing the TM capacity with commodities.

Affected area	Earthquake test case		Hurricane test case	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
a_1	21,000	6,000	5,000	8,000
a_2	9,000	24,000	5,000	2,000

Table 2.   **Demand for commodities by test case and scenario [tons]**

c.   *Ramp Space*

RS is required by all air TM. For example, a CH-53 needs RS in order to land and deliver commodities to an AA. See Table 3.

Affected area	Initial capacity for ramp space [tons]	Max expansion for ramp space [tons]	Variable expansion cost for ramp space [$/ton]
a_1	2,000	10,000	2,000
a_2	1,000	20,000	1,000

Table 3.   **Ramp space attributes for all test cases**

We have assumed some differences in RS at the AAs:

- Initial RS capacity at a_1 is twice that of a_2.

- Maximum RS expansion for a_2 is twice that of a_1.

- Variable RS expansion cost of a_1 is twice that of a_2.

4.   **Relief Locations**

A RL can be an air base, a military headquarters, a warehouse or a medical facility with all its components; aircrafts, vehicles, commodities, and doctors. Table 4 shows the data used for RLs. A discussion follows:

a.   *Air Bases and Military Headquarters*

This is the start and drop-off location for any TM. TM can be land-, air-, or sea-based. An air base or a military headquarters may have all or a combination of TM. For example, during the relief operation, an air base can also be used as a starting location for trucks; an open area within a military base can be converted into a landing area for helicopters, thus catering to land helicopters. Its medical facilities can also be used to treat PSs. In our test cases, we assume all TM are able to start and drop-off at every RL, but our model easily accommodates restrictions that may be applicable to other cases.

b.   *Warehouses*

Commodities like food, water, daily human hygiene and medication for homeless people are aggregated in this model. These commodities are kept in warehouses and cater to the AAs. They can only be transported only by TM configured for general mission.

c.   *Medical Facilities*

In this model, we have aggregated doctors, nurses, medical facility's administrative personnel, medication requirements, surgery room requirements and emergency room requirements as HP.

Every PS is assumed to be healthy once they are evacuated from AA and transported to a medical facility. We assumed each HP can handle up to five PSs.

d.   *Differences between Relief Locations*

We assumed four RLs in our test cases. Two of them are located in urban areas and two are in rural areas, with the following differences:

- l_1 and l_2 (urban areas):

    - Variable warehouse expansion cost in l_1 and l_2 is twice that of l_3 and l_4.

- l_3 and l_4 (rural areas):

    - Initial capacity for both medical facilities and warehouses is twice that of l_1 and l_2.

    - The maximum expansion for both medical facilities and warehouses is twice that of l_1 and l_2.

    - Medical facility variable expansion cost is twice that of l_1 and l_2.

Attribute	Earthquake test case				Hurricane test case			
	Relief location				Relief location			
	l_1	l_2	l_3	l_4	l_1	l_2	l_3	l_4
Initial capacity for warehouses [tons]	2,000	3,000	4,000	6,000	1,000	1,500	2,000	3,000
Maximum expansion for warehouses [tons]	4,000	4,000	8,000	8,000	4,000	4,000	8,000	8,000
Variable expansion cost for warehouses [$/ton]	690	690	345	345	1,380	1,380	690	690
Initial capacity for medical facilities [HP]	300	300	600	600	150	150	300	300
Max expansion for medical facilities [HP]	1,000	1,000	2,000	2,000	1,000	1,000	2,000	2,000
Variable expansion cost for medical facilities [$/HP]	1,250	1,250	2,500	2,500	2,500	2,500	5,000	5,000

Table 4.   **Attributes for the relief locations**

5.   Transportation Means

In our test cases, we consider three types of TM. We use two types of aircraft (CH-53 and MV-22) and one type of truck (HMMWV). CH-53S and MV-22S are configured for "special" mission and CH-53G and MV-22G are configured for "general" mission. They are able to handle tasks like rescuing PSs and delivering commodities, respectively. HMMWV can only deliver commodities. See Table 5.

a.   *Daily Operating Hours for Transportation Means*

We limit the operation for all TM to 20 hours per day. The remaining four hours are assumed for gas refill and change of shift for the flight and land operators. We model the three-day surge period by setting total operating hours per TM to 60 hours. We also assume that TM are ready to use and no maintenance issues or breakdowns occur.

b.   *Travel Time of Transportation Means*

Travel time is calculated based on the TM's speed and the distance from each RL to each AA. For example, a MV-22 is 1.6 times faster, and a HMMWV is five times slower than a CH-53. See Tables 6 and 7. l_1 and l_2 are assumed to be closer to all AAs.

Attribute	Transportation Means				
	CH-53S	CH-53G	MV-22S	MV-22G	HMMWV
Availability [# of units]	20	20	15	25	100
Maximum expansion [# of units]	20	20	20	20	200
Variable expansion cost [$ / ton]	500,000	500,000	800,000	800,000	2,000
Commodity capacity [tons]	0	18	0	18	1
Survivor Capacity [# of survivors]	24	0	12	0	0
Worker Capacity [# of workers]	0	55	0	24	8
Daily available hours [hours]	60	60	60	60	60
Operating range [hours]	8	8	10	10	14

Table 5.   **Attributes for all transportation means**

	CH-53		MV-22		HMMWV	
	Affected area		Affected area		Affected area	
Relief location	a_1	a_2	a_1	a_2	a_1	a_2
l_1	20	40	12.5	25	100	200
l_2	40	20	25	12.5	200	100
l_3	60	80	37.5	50	300	400
l_4	80	60	50	37.5	400	300

Table 6.   **Travel time (in minutes) for all transportation means in earthquake test case**

	CH-53 (both scenarios)		MV-22 (both scenarios)		HMMWV			
					Scenario 1		Scenario 2	
	Affected area		Affected area		Affected area		Affected area	
Relief location	a_1	a_2	a_1	a_2	a_1	a_2	a_1	a_2
l_1	20	40	12.5	25	100	na	na	Na
l_2	40	20	25	12.5	na	100	na	Na
l_3	60	80	37.5	50	300	400	na	Na
l_4	80	60	50	37.5	400	300	na	Na

Table 7.   **Travel time (in minutes) for all transportation means in hurricane test case**

6.   Budget

"In fiscal year 2004, the average budget for a state emergency management agency was $40.8 million, a 23 percent reduction from fiscal year 2003." [PA, 2005]. We use this estimated budget ($40 million) for all of the disaster test cases.

7. Scenario Likelihood

We assume "Scenario 1" occurs with a probability of 25%, and "Scenario 2" occurs with a probability of 75% for both test cases.

B. DIFFERENCES IN DATA AND ASSUMPTIONS

The following sections discuss the differences between the two test cases and scenarios.

1. Earthquake Test Case

In this test case, we suppose the earthquake strikes an urban area. We create two hypothetical scenarios and the differences are the number of PSs and the demand for commodities in each AA. We also suppose all roads leading to an AA are passable to land means in both scenarios.

For scenario one, the epicenter of the earthquake occurs close to a_1, thus a_1 sustains more damage than a_2. This results in more PSs and higher demand for commodities. Scenario two has the opposite situation: more severe damage in a_2.

The total number of PSs is based on the estimated fatalities of the 2005 Pakistan earthquake [Wikipedia, 2006]. The demands for commodities are estimated from the number of homeless people.

2. Hurricane Test Case

In this test case, we suppose a hurricane strikes a rural coastal area. In scenario one, we assume both a_1 and a_2 suffer the same damage. For scenario two, the hurricane hits a_2 first and then a_1. Therefore, a_2 sustains more damage than a_1.

The settings for both scenarios are similar to the earthquake scenarios except for the following differences:

- The occurrence of a hurricane is usually more predictable than the occurrence of an earthquake and preparations (e.g., evacuation before the hurricane strikes) can be made in advance. Therefore, the number of PSs and demand for commodities are lower for a hurricane than for an earthquake.

- Due to flooding, some roads in scenario one (e.g., traveling from l_1 to a_2 and l_2 to a_1) are impassable to all land means.

- Severe flooding happened in scenario two; therefore all roads are impassable to all land means.

- The initial capacity of warehouses in the hurricane test case is half of that in the earthquake test case.

- Variable costs of expansion for HP and warehouses in the hurricane test case are twice as those in the earthquake test case.

The number of PSs and demand for commodities information are from Hurricane Katrina [Wikipedia, 2005].

IV.   RESULTS

This chapter presents the results to our two-stage stochastic POM for the earthquake and the hurricane test cases described in Chapter III. We also compare the stochastic solution with the deterministic wait-and-see bound, to obtain the Expected Value of Perfect Information (EVPI) and obtain a heuristic solution which provides the Value of the Stochastic Solution (VSS), see Birge and Louveaux [1999].

Essentially, the wait-and-see bound represents an upper limit for our model. It is obtained by assuming we have perfect information on which disaster is going to happen, so we can plan our RUAs accordingly. EVPI is the difference between the stochastic solution to POM and the expected value of all individual solutions for each scenario under perfect information. EVPI is useful to provide insight on how many more survivors could be rescued, on average, if perfect information to plan for the specific disaster were available.

The heuristic solution is obtained by solving a deterministic POM which plans for a hypothetical "average" scenario. Values of the first-stage decision variables are then fixed in the model to provide different solutions for each actual scenario. VSS is the difference between the stochastic solution to POM and the heuristic solution objective function. By construction, this solution is sub-optimal, yet still difficult to obtain without POM.

All the computations are executed on an Intel ® Xeon^{TM} CPU, 3.73 GHz computer with 3 Gb of RAM running under Microsoft Windows XP operating system. The optimization models are coded in General Algebraic Modeling System [Brooke et al. 1998] and solved by CPLEX 9.0 [ILOG, 2004].

In the next sections, our analysis is focused on the strategic decisions regarding the allocation of the available budget for expansion.

A. EARTHQUAKE TEST CASE

1. Result Summary

Figure 2 shows the result for rescued survivors, casualties due to unmet demand for commodities, and the total objective function representing a weighed average of the two values. The wait-and-see bound yields an optimistic bound (-94,563) on the best possible implementable solution (-102,988) provided by our stochastic solution to POM. This gives an EVPI of -8,425, or 9% worse than if perfect information were available. On the other hand, if our strategic decisions are driven by the "average" scenario, we find a heuristic solution (-114,981), which yields a VSS of -11,993, or 12% worse than the optimal stochastic solution.

The difference between the solutions will be explained later with additional results.
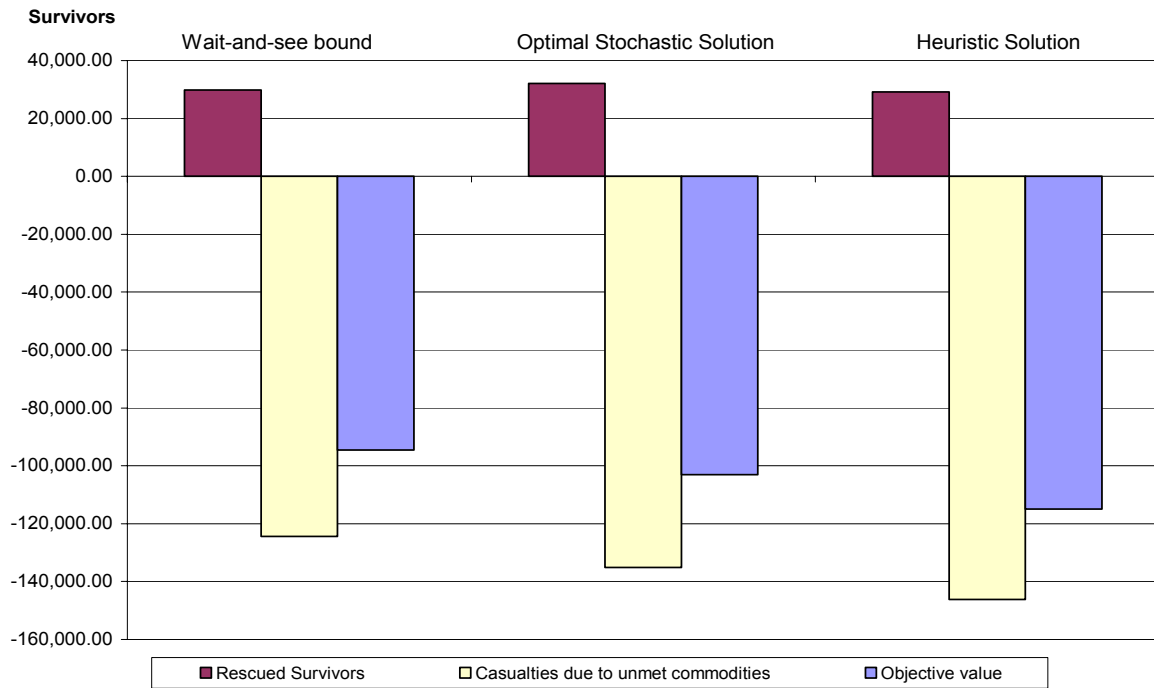

Figure 2.   **Objective Function Breakdown (Earthquake test case). EVPI and VSS are 9% and 12% respectively, of the stochastic solution.**

Figure 3 shows the breakdown of the total budget ($40 million). All budget is spent in all scenarios and models. Expenses in warehouse expansion are the least in all models, followed by health personnel.
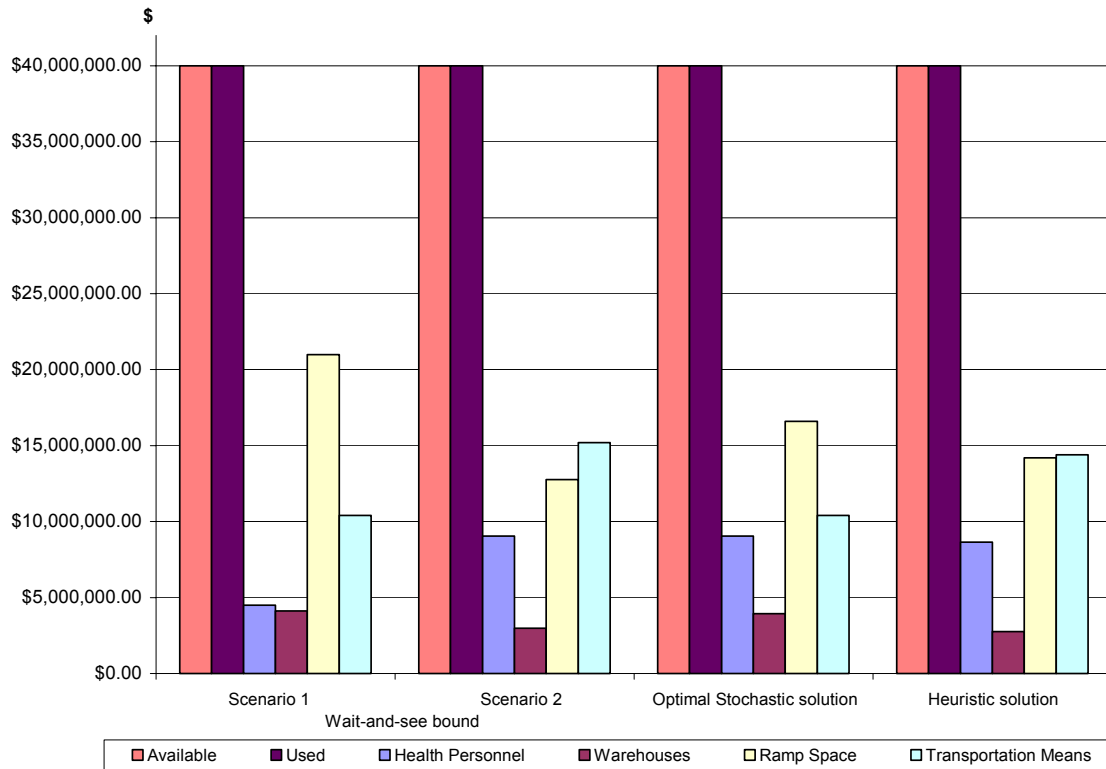

Figure 3.　　**Budget Expenditure Breakdown (Earthquake test case)**

Table 8 shows the summary of the first-stage decisions on assets that are being expanded.

First Stage Decision	Wait-and-see bound	% used	Optimal Stochastic solution	% used	Heuristic solution	% used
Health Personnel (total expanded)	20,814	69%	23,104	77%	22,285	74%
Health Personnel (maximum expandable)	30,000		30,000		30,000	
Warehouses (total expanded) [tons]	5,234	22%	5,715	24%	4,000	17%
Warehouses (maximum expandable) [tons]	24,000		24,000		24,000	
Ramp Space (total expanded) [tons]	13,199	44%	12,341	41%	14,197	47%
Ramp Space (maximum expandable) [tons]	30,000		30,000		30,000	

Table 8.   **Summary of First-stage Decisions (Earthquake test case)**

2.   Findings

The negative values for the objective function shown in Figure 2 are due to the heavily penalized unmet commodities: Only 55% and 49% of commodities are delivered in the stochastic and heuristic solutions, respectively. Additionally, only 32% and 29% of PSs are rescued in the stochastic and heuristic solutions, respectively. Various factors such as a high number of PSs, a high demand for commodities and limited numbers of TM have contributed to this result. It is observed from Table 8 that all expansions in this test case are not under the maximum possible; therefore, budget can be identified as the limiting factor.

We also notice that RS expansion by the heuristic solution is 6% more than in the stochastic solution. However, from Figure 3, the heuristic solution has spent 14% less in RS than the stochastic solution. This apparent contradiction is caused by the higher demand of commodities in a_2. We also note that the 14,197 tons of RS expansion by the heuristic RS expansion occur only at a_2. An average scenario is used for the heuristic

solution and this drives the solution to be skewed toward optimizing for the second scenario. This result shows planning based on an average scenario is less desirable than using an optimal stochastic approach.

B.   HURRICANE TEST CASE

1.   Result Summary

The wait-and-see bound yields an optimistic bound (13,506) on the best possible implementable solution (10,082) provided by our stochastic solution to POM. This gives EVPI of 3,424, or 25% worse than if perfect information were available. On the other hand, using a heuristic solution (-1,348) yields VSS equal to 11,431, or 113% worse than the optimal stochastic solution. See Figure 4.

Survivors

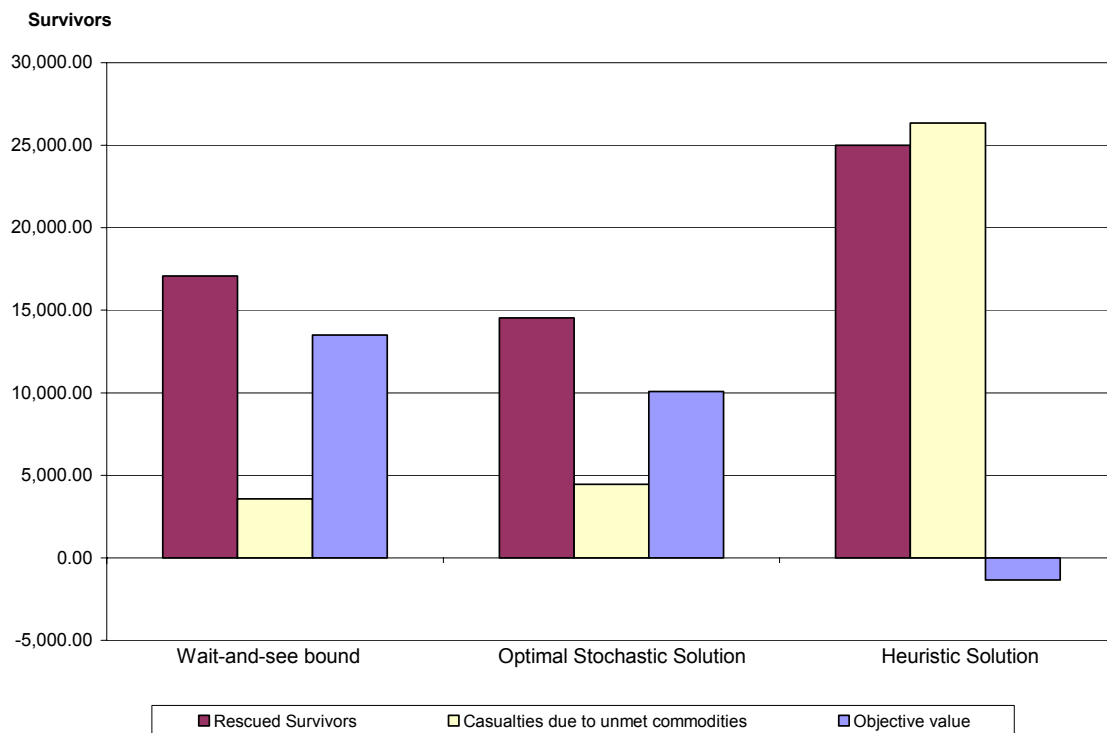| Legend	
■ Rescued Survivors	□ Casualties due to unmet commodities
□ Objective value	

Figure 4.   **Objective Function Breakdown (Hurricane test case). EVPI and VSS are 25% and 113% respectively, of the stochastic solution.**

Figure 5 shows the breakdown of the total budget ($40 million) for the hurricane test case. All budget is spent in all scenarios and models except by the heuristic model. The wait-and-see bound and stochastic solution use most of its budget on the expansion of RS whereas the heuristic solution spends most of its budget on TM.
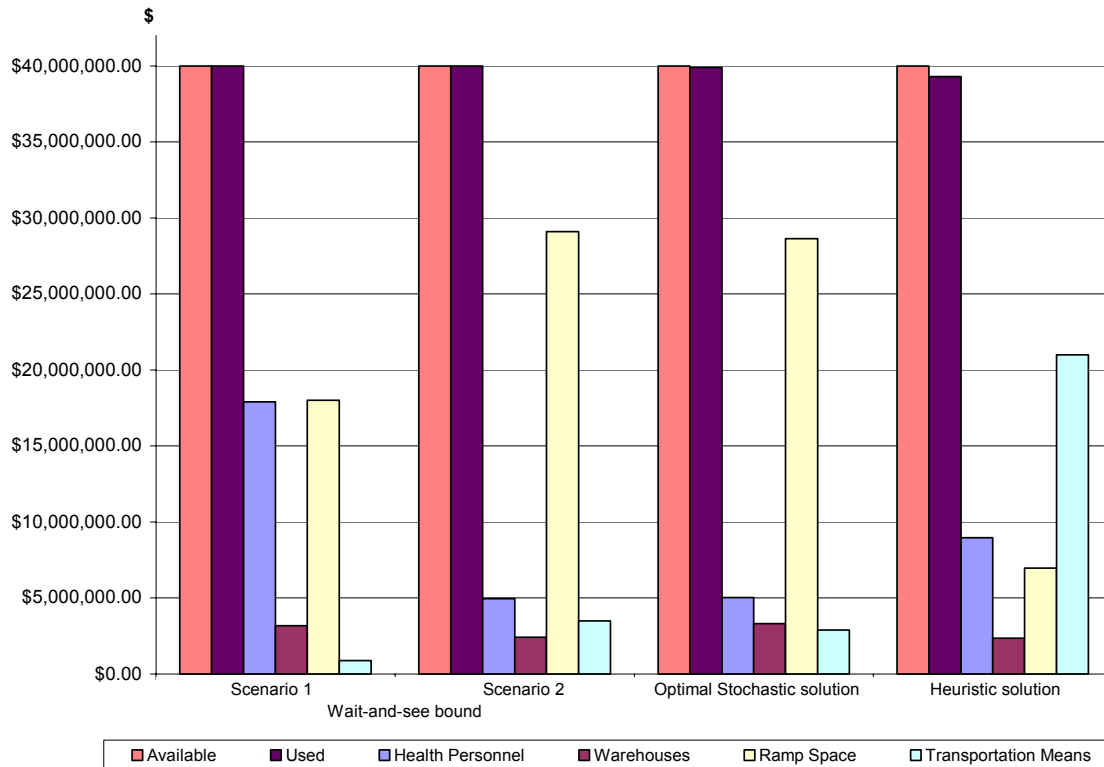

Figure 5.   **Budget Expenditure Breakdown (Hurricane test case)**

Table 9 shows the summary of the first-stage decisions on assets that are being expanded.

First Stage Decision	Wait-and-see bound	% used	Optimal Stochastic solution	% used	Heuristic solution	% used
Health Personnel (total expanded)	12,576	41%	10,042	33%	20,444	68%
Health Personnel (maximum expandable)	30,000		30,000		30,000	
Warehouses (total expanded) [tons]	5,234	22%	5,715	24%	4,000	17%
Warehouses (maximum expandable) [tons]	24,000		24,000		24,000	
Ramp Space (total expanded) [tons]	7,619	25%	7,907	26%	2,488	8%
Ramp Space (maximum expandable) [tons]	30,000		30,000		30,000	

Table 9.   **Summary of First-stage Decision (Hurricane test case)**

2.   Findings

Figure 4 clearly shows that using a stochastic approach has substantial advantage over deterministic solutions. The heuristic solution fails to identify the consequences of unmet commodities, although it tends to rescue more survivors than the stochastic solution.

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V. CONCLUSIONS AND FUTURE WORK

We have formulated and solved a two-stage, linear, mixed-integer Pre-positioning Optimization Model (POM) to provide guidance in pre-positioning of the Relief Units and Assets' (RUAs). The model takes into account physical limitations, such as the capacity of Transportation Means (TM), and other logistic and operational constraints in order to maximize the expected rescued survivors and the delivery of required commodities over the surge period.

Two fictitious disaster test cases (earthquake and hurricane) have been tested. To account for different levels of damage, we use several scenarios for the number of Potential Survivors (PSs) and the demand of commodities in each test case. To add further realism, we have also assumed some routes are impassable in some scenarios of the hurricane test case.

In both test cases, the stochastic solution improves the deterministic solution, based on the optimal plan for an average scenario, by approximately 11,000 rescued survivors. This accounts for almost 11% of the total PSs in the earthquake test case and 37% in the hurricane test case.

The available budget is exhausted in both test cases, whereas expansion of possible sites is not maximized. This suggests budget is the limiting factor for the deficit in the number of rescued survivors and unmet demand in our test cases.

Future analyses and testing may improve the model and data in order to achieve further realism. Some possible areas for research include:

- Employing real data as estimated by experts in the area of disaster relief planning.

- Testing the robustness of the stochastic solution with respect to each individual scenario, and its sensitivity to changes in the data.

- Incorporating alternative objective functions in POM. Currently, the aim is to maximize the expected rescued survivors. Other plausible objectives could be minimizing the total budget given a desired level of performance.

- Incorporating the PSs' health deteriorating while they wait to be rescued. In the current model, we assume there is no health deterioration. The model can be further extended to incorporate the survivability curve of a PS after a disaster, as well as priorities among PSs.

- POM can be enhanced by incorporating the dynamics of the relief operation over time. For example, the delivery of commodities extends beyond the surge period at a certain rate until all requirements are met.

- Introducing further survivor classification. There are two classes of survivor in this thesis: PSs and homeless people. However, in disaster like Hurricane Katrina, survivors can be relocated out of the disaster area. Therefore, a survivor can be further classified into another category: survivors that need to be relocated to another area, but do not need medical attention.

- Changing TM operating patterns. TMs are assumed to travel from a relief location (RL) to an AA and back to a RL (not necessarily the same). A more reasonable operating pattern is to pick up PSs from different AAs (until the TM's capacity is reached) and then return to a RL.

- Introducing a fixed expansion cost. In order to accurately model the site expansion, a fixed expansion cost needs to be introduced. It can be added to warehouses, medical facilities and each AA's ramp space. Similarly, a minimum expansion, if any expansion occurs, is sometimes a requirement.

- Providing a graphical user interface to facilitate the input of data and display of results. In this way, POM may be used by personnel involved in disaster relief planning who are not familiar with optimization techniques.

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